






Measurement of Organizational AI Exposure: An AI-Assisted Comparative Approach in the Algerian Insurance Industry

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Abstract.

This study aims to measure and analyze the organizational AI exposure in two different Algerian insurance companies, SAA and Alliance, using a proposed conceptual framework within an AI-assisted comparative case approach to assess AI Exposure through three core dimensions: process, administrative, and competitive exposure. The results from the strategic matrix show that Alliance is positioned within a controlled exposure configuration due to its high internal capabilities (83.65%) and low external pressure (46.6%), reflecting a voluntary and active adoption. In contrast, SAA is positioned at the boundary between defensive exposure and total exposure, characterized by moderate internal exposure (60.4%), high competitive pressure (73.2%), and limited administrative exposure (53%). this study suggests reinforcing digital sovereignty, prioritizing skills upgrading, and adopting flexible administrative models before making extensive investments in artificial intelligence.

Keywords: Artificial Intelligence Exposure, Insurance, process exposure, administrative exposure, competitive exposure, SAA, Alliance Assurances.

1 Introduction

Artificial intelligence has become a key driver of digital transformation [21], particularly in data-intensive industries such as insurance [5] [12]. While AI models, in insurance, have proven superior performance [12] [2], companies face profound organizational and workforce transformation. However, in the Algerian context, the insurance industry still lacks a systematic diagnosis and precise assessment of AI Exposure, particularly regarding differences between public and private companies. Accordingly, this study addresses this gap by examining AI Exposure in SAA and Alliance through this central research question:

What is the organizational status of AI Exposure in SAA and Alliance from an analytical approach to the recent managerial literature?

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To explore this research problem, the study addresses these following sub-questions:

- What are the dimensions of AI exposure based on the specialized literature?
- Is there a difference between the exposure in SAA and Alliance in the context of the digital transformation?

2 Literature Review

Generally, exposure is defined as the likelihood of AI affecting a particular sector of the economy, either positively or negatively [23]. Most studies conceptualize exposure at the task and occupational level, reflecting how AI enhances or replaces employees' tasks [10] [27] [8], specifically in sectors characterized by intensive information processing, such as finance and insurance [10] [9] [19]. Workforce composition and firms' ability to attract technical talent have also been identified as key indicators of AI Exposure [1]. Several other studies have explained how the managers' attitude, structures, systems, processes, and considerable personal changes, serve as indicators for AI Exposure [6] [3] [13] [14]. Moreover, recent studies extend AI Exposure to the competitive level, demonstrating that AI-driven automation, delayed adoption in customer-oriented processes, and unequal access to AI systems increase the AI Exposure [27] [11] [17]. However, most existing approaches focus on occupational or sectoral exposure, while firm-level measurement frameworks remain relatively limited.

3 Methodology

3.1 The Proposed Conceptual Framework

The proposed conceptual framework of this study is depicted in figure 1.

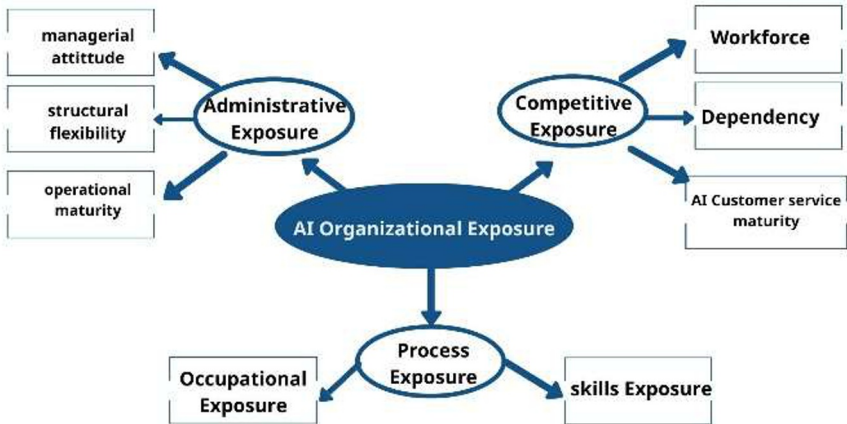


Fig. 1. The Proposed Conceptual Framework.

Source: Authors' own work

3.2 Epistemological Positioning and Adopted Approach

Due to the exploratory nature of this study and the lack of structured data, an AI-assisted comparative case approach was adopted within a post-positivist epistemological perspective [25]. The indicators represent context-dependent analytical estimates, aiming for analytical and theoretical generalization rather than statistical generalization.

3.3 Evaluation Protocol and Sensitivity Analysis

This analysis was used to ensure that results are not resulting from algorithmic bias, and to address the lack of direct field measurements [22]. It aims to test the robustness organizational positioning of the selected companies on the proposed analytical matrix by examining the stability of the resulting rankings under uncertainty, using the scenario-based sensitivity analysis [18] [22] [22] [26], with a margin of error of 10% as a conservative analytical assumption for robustness test. Three scenarios were examined for each company (baseline, optimistic, and pessimistic), while keeping contextual prompts and evaluation rules constant. Thus, the results showed that the stability organizational positioning of two companies across all scenarios, which ensure the robustness and indicate that the observed differences reflect structural organizational characteristics rather than minor estimation fluctuations.

3.4 Sampling Strategy and Data Collection

A purposive theoretical sampling was adopted, whereby two companies were selected, SAA (Société National d'Assurance) and Alliance Assurance, to reflect the variation in ownership (public/private), organizational structure, declared digitalization level, human resource management style, in order to maximize the explanatory potential of the comparative analysis.

The analytical and secondary tools used in this study are: **organizational documents** such as job descriptions, task manuals, and annual reports, as well as international standardized databases such as O*NET and AI exposure Index, and **AI supported analysis** used to extract the indicators from predefined resource, not as a producer of knowledge. Finally, to ensure the methodological rigor, and to mitigate the concerns of **AI hallucinations**, a strict human oversight was conducted through the controlled AI prompts and the manually reviewing of numerical values.

3.5 Methodological Procedures

The study adopted a task-level exposure approach [7] [9] to measure occupational exposure by decomposing each occupation into basic tasks and assessing their suitability for automation or enhancement with AI on a three-point scale (0 = non-automatable, 0.5= augmentable, 1= automatable), then calculating the weighted AIOE index. The skill exposure index was also constructed based on the literature [1] and converted into a quantitative scale, 0-25 points. Administrative and competitive exposure were quantified using evidence-based scoring to convert qualitative indicators into numerical scores, a 10- and 5 points, respectively, was used, with score of 5/10 adopted as a neutral reference point following:

$$\text{Score} = \text{base score} + \text{positive evidence} - \text{negative constraints}$$

4 Analysis, Results & Discussion

4.1 Results

Process AI Exposure Results.

It encompasses both the occupational and the skills AI exposure:

Occupational AI Exposure.

Since this dimension represents the extent of routine tasks can be supported by AI, the weighted AIOE index of SAA reached 78.06%, indicating high exposure levels ranging between 0.9-0.95 for job tasks such Admin & Clerks, Underwriters, Actuaries and IT. Whereas claims adjusters' tasks show the lowest AI exposure level of 0.6, this job is primarily human-centric tasks, such as on-site inspection and negotiation, which are currently difficult for AI to perform (table 1).

Table 1. Calculation of the Occupational AI Exposure.

Occupation Title	Employment N	Employment Weight W %	AIOE Score SE	N*SE	Weighted AIOE W*SE
SAA					
Sales Agents	1030	31.52	0.78	803.4	0.25
Underwriters	600	18.36	0.9	540	0.16
Claims Adjusters	980	29.99	0.6	588	0.18
Admin & Clerks	550	16.83	0.95	522.5	0.16
Actuaries & IT	108	3.30	0.9	97.2	0.029
TOTAL	3268	100		2551.	0.78=78
				1	%
Alliance					
Direction Technique	50	10%	0.9	45	0.09
Network Animation	100	21%	0.65	65	0.14
Claims-Sinistres	170	35%	0.7	119	0.25
Finance & Admin	90	19%	0.95	85.5	0.18
IT / DSI	70	15%	0.9	63	0.13
TOTAL	480	100%		377.5	0.79=79
					%

Note: $AIOE_{Alliance} = \frac{\sum(N \times SE)}{\text{Total Employees}} = 0.79$ $AIOE_{SAA} = \frac{\sum(N \times SE)}{\text{Total Employees}} = 0.78$

Scores are classified into low (0.00-0.35), indicating no immediate need for AI investment and continued reliance on human input; moderate (0.36-0.70) reflecting opportunities for AI supported augmentation and workforce upskilling; and high (0.71-1.00), signaling strategic urgency requiring organizational restructuring and immediate automation adoption. Prepared by authors based on CNA insurance market report (2022), O*NET online database, and SAA annual report (2022).

The data for Alliance Company indicate a high level of AI Exposure accounting for 79%. For instance, the finance, administrative, and IT/DSL roles rank among the most AI Exposed, with a score between 0.95-0.9. While the network animation role shows the lowest level of exposure, scoring 0.65.

Skills AI Exposure.

The results from the table 2 reveal a significant difference between SAA and Alliance. Alliance records high average scores in terms of junior agility shift, flexibility and density of technical skills, while SAA’s human competences suffer from a gap in information processing and change agility skills.

Sub-dimension	Indicator	SAA	Alliance
Tech Roles Density	Share of employees in IT, data, innovation departments compared to the total employment	14	22
Educational Attainment	Share of employees with advanced degrees (master’s and PhD)	18	20
Info Processing Intensity	Degree of digitalization of daily operations	15	23

Junior Agility Shift	New employees average age + technical skill currency	10	24
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Table 2. Comparison of skills exposure

Note: indicators are scored on 0-25 scale, where 0-10=low, 10-18=moderate, 19-25=high AI exposure. Prepared by authors based on job requirements published by SAA (2024) and ALLIANCE (2024) on LinkedIn.

From the above, we can calculate the AI process exposure Index through the following proposed equation:

$$\text{AI Process Exposure} = \frac{(\text{Skills Score} + \text{Occupational Score})}{2} \times 100$$

The results from table 1 and 2 were used to calculate the AI Process Exposure, which was estimated at 67.5% for SAA, and 84% for Alliance. This indicates a sharp gap between the two insurance companies.

Administrative AI Exposure Results.

Administrative exposure was measured based on three elements: administrative position, structural flexibility, and operational maturity. The results reported in table 3 indicate significant differences between SAA (53%) and Alliance (83%).

Table 3. Comparison of the AI administrative Exposure.

Sub-dimensions	SAA	Alliance
Managerial attitude	8.5/10 = 85% Radical, positive	9.5/10 = 95% Strategically aligned.
Structural flexibility	3/10 = 30% Flat and agile, High flexibility.	8/10 = 80% Rigid and heavy hierarchy.
Operational maturity	4.5/10 = 45% Partial digitalization	7.5/10 = 75% Advanced/automated
Average	53.33%	83.33%

Note: 0-3 high risk: rigid structure, manual operations, and resistance to change. 4-6 transitional phase: partial digitalization, traditional structure, and positive intention. 7-10 high readiness: radical leadership, agile structure, and advanced digitalization. Prepared by authors based on data collected through AI-assisted information extraction process from publicly available reports and sources.

While SAA’s leadership is strategically supportive of digital transformation (85%), its progress is significantly constrained by rigid, hierarchical structure, and a transitional level of operational maturity, Conversely, Alliance demonstrates a proac-

tive, entrepreneurial leadership with an agile, flat organization and advanced operational automation.

Competitive AI Exposure Results.

The competitive exposure Index assesses the companies' vulnerability to competitive and technological pressures across three dimensions.

Table 4. Comparison of AI Competitive Exposure

The sub-dimension	SAA	Alliance
AI customer service maturity	5/5 Traditional services, lack of automated customization.	2/5 advanced applications, responsive, but lacks affective computing capabilities.
workforce adaptability	5/5 high exposure: legacy recruitment model, struggling to attract tech talent.	2/5 agile model, partnership with startups and universities.
Model dependency	1/5 sovereign cloud infrastructure (partnership with Algerie Telecom)	3/5 reliance on partners with potential Closed APIs
Competitive Exposure Index	3.66: high risk	2.33: low-moderate risk
Exposure %	73.2%	46.6%

Note: indicators are rated on a 1-5 scale; the exposure index represents the arithmetic mean of the sub-indicators. (1-2) low, (2-3) moderate, (3-5) high. Prepared by authors based on data collected through AI-assisted information extraction process from publicly available reports and sources.

As shown in table 4, SAA records higher exposure scores in the dimensions of customer service maturity and workforce adaptability. In contrast, Alliance records lower scores in both dimensions. With regard to technology dependency, SAA records a lower level, whereas Alliance shows higher dependence on external technology partners.

Comparative AI Exposure Profile: SAA vs. Alliance.

The aggregate exposure score for each company was calculated using arithmetic average of the three exposure dimensions. SAA recorded a level of 64.6%, while Alliance exhibited a score of 71.23%

Furthermore, Fig. 2. reveals two radically different strategic situations. Alliance shows high administrative (83%) and process (84%) exposure, indicating a deep internal integration of AI. Conversely, SAA's profile leans towards the competitive axis (73.3%), while its management exposure remains significantly low (53%).

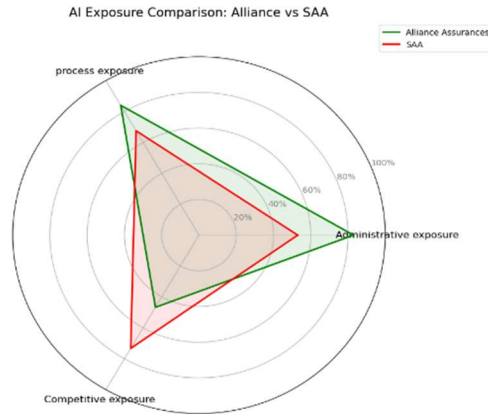


Fig. 2. Comparative AI Exposure Profile: SAA vs. Alliance.
Source: Authors' own work

4.2 Discussion

Although the results reflect high AI occupational exposure scores for the two companies, this similarity masks a fundamental divergence in the nature of exposure. High exposure at SAA reflects substitution effects driven by routine tasks, whereas at Alliance it indicates augmentation and complementarity patterns based on knowledge-intensive roles.

Despite the convergence in skill exposure, especially in terms of cognitive component, this similarity does not extend to the nature of the applied skills. At Alliance, employee skills are intensively directed to digital processes and data acceleration, supported by structural flexibility and young factor, which transform the occupational exposure from substitution pattern to the augmentation one. While SAA faces the risk of skill obsolescence, the persistence of legacy roles, structural rigidity, and a relatively older workforce.

In light of the previous analysis, the AI process matrix (figure 3-A) was used as an analytical interpretive tool to understand the nature of AI exposure. Alliance is positioned in the leadership area, where high skill intensity coincides with a high level of operational exposure to automation, creating what can be described as a form of organizational digital resilience. The surplus of skills enables ALLIANCE to transform technological exposure from an external pressure into an internal strategic asset. AI applications tend to follow an augmentation logic, whereby intelligent systems support employee productivity and enhance human capabilities rather than replace them. This positioning is further reinforced by a relatively flexible organizational structure and faster decision-making process, which allow administrative exposure to function as an enabling factor that accelerates digital transformation. In contrast, SAA falls into the zone of the structural fragility as a result of imbalance between the high automation pressure and the skills deficit, which make it vulnerable to a forced substitu-

tion and job lost, whereby intelligent systems are primarily adopted to reduce operational costs and handle large volumes of routine processes and data-processing tasks. The main challenge faced by SAA does not lie in the presence of technological exposure itself, but rather in the existence of a skill gap that limits the firm’s capacity to absorb and manage this transformation. Thus, it requires fundamental structural reforms before making any significant investment in Artificial Intelligence.

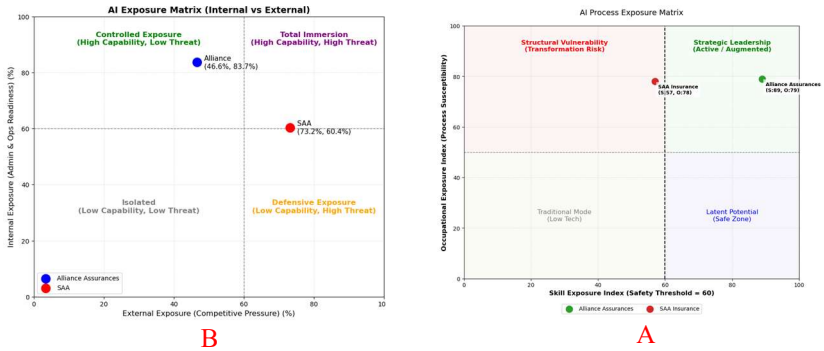


Fig. 3. Strategic positioning matrix of AI Process Exposure and internal/external exposure of SAA and Alliance. The Latent zone is a strategic future zone for the creative industries. Strategic Leadership (Skills >60%, Exposure >50%): high readiness enables augmentation and value creation; Structural Vulnerability (Skills <60%, Exposure >50%): skill deficits lead to forced automation and structural risk; Latent Potential (Skills >60%, Exposure <50%): strong capabilities remain underexploited; Traditional Mode (Skills <60%, Exposure <50%): low exposure and weak skills sustain traditional operations.

Regarding AI Competitive Exposure, SAA is positioned within the **high-risk zone**, due to its traditional and non-customized services, which make it more exposed to its AI-enabled competitors. It also faces difficulties in attracting technical talents due to its traditional employment structure. Its only strength is the partnership with Algeria Telecom and the reliance on local date, which protect them from the risks of the external dependency. Comparatively, Alliance lies within the **relative competitive safety zone**, having advanced applications and quick response to customers, which reduce the risk of losing customers. Alliance relies on agile model and partnerships with startups and universities, ensuring the continuous of tech skills. In addition, on external technology partners and closed APIs, putting it at the risk of dependency on technology suppliers.

To synthesize the interaction between operational, administrative, and competitive exposure this paper developed the internal-external matrix shown in **fig.3.B**. It reveals that the difference between SAA and Alliance is not so much about their exposure levels as it is about their strategic logic. Using the 60%threshold as a benchmark for strategic action, the results indicate that once this level is exceeded, AI exposure necessitates immediate organizational change, whether driven by internal initiative or external market pressure. Alliance is positioned within a **controlled exposure con-**

figuration due to its high internal capabilities (83.65%) and low external pressure (46.6%) which reflects a voluntary and active adoption. In contrast, SAA is positioned at the boundary between the **defensive exposure** and the **total exposure**, its moderate internal exposure (60.4%), coupled with a highly competitive pressure (73.2%) and limited administrative exposure (53%). This positioning confirms that it is the nature of AI exposure is the decisive factor in explaining the divergence of the digital transformation between the two companies.

Consequently, the comparative analysis reveals that the differences between the two studied cases not only reflect variation in the overall AI Exposure, but also differences in the organizational logic of AI exposure construction. This confirms the importance of distinction between the exposure resulted from an internal organizational initiative and the exposure by the external pressures. It is important to note that this classification does not serve as a sector-wide generalization; rather, it is a description of each case's relative positioning within the proposed analytical matrix.

5 Conclusion & Recommendations:

This study concludes that the AI Exposure in SAA and Alliance differs depending on the process, administrative, and competitive dimensions.

at the process level, the core difference between the two companies does not lie on the nature of automated-prone but rather in the skill response gap. The human resources with technical skills are the decisive factor in transforming the AI Exposure from a substitutional threat to an augmentation opportunity. Regarding the AI Administrative Exposure, the organizational structure is the critical factor influencing the operational maturity, agile structures accelerate the digitalization, the traditional hierarchical constrain it. Turning to the AI Competitive Exposure, a **key paradox** emerges, whereas the digital agility provides a competitive performance in customer service and talent acquisition, it increases the risk of technology dependency to the external suppliers. Based on the foregoing, this study suggests prioritizing the skills upgrading before AI adoption, adopting flexible and agile organizational structures, and reinforcing the digital sovereignty to reduce the dependency on external technologies and ensure data security.

Despite the methodological rigor adopted in this study, and the empirically grounded insights provided for both researchers and practitioners, several limitations should be acknowledged. First, the study is limited by the selection of a small sample of companies, which leads us to avoid the statistical generalization. Second, since the indicators were inherently estimation-based, using secondary data available from digital sources and processed using AI systems, it did not incorporate the internal, non-disclosed data of selected companies. Future studies must concentrate on analysis of the algorithmic errors in the Algerian insurance sector in the absence of a legal framework governing the AI Exposure of these companies, and measurement of the return on investment in artificial intelligence within insurance companies, specifically the comparative analysis between exposure costs and workforce retention costs.

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